# Enhancing Walking Experience: A Walking Route Recommendation System Considering Nearby Spots

Katsuyuki Yamauchi
*Kyoto Sangyo University*
Kyoto, Japan
i2186195@cc.kyoto-su.ac.jp

Da Li
*Fukuoka University*
Fukuoka, Japan
lida@fukuoka-u.ac.jp

Panote Siriaraya
*Kyoto Institute of Technology*
Kyoto, Japan
spanote@kit.ac.jp

Yukiko Kawai
*Kyoto Sangyo University*
Kyoto, Japan
kawai@cc.kyoto-su.ac.jp

Shinsuke Nakajima
*Kyoto Sangyo University*
Kyoto, Japan
nakajima@cc.kyoto-su.ac.jp

***Abstract*—In recent years, there has been a noticeable increase in the population embracing walking as a means of weight management and overall physical well-being. However, many users perceive walking as a daunting task and find it challenging. Therefore, making walking an enjoyable activity has become increasingly significant. In light of this, we are developing a walking support system designed to engage users with various characteristics. This paper presents an analysis of user reviews for gourmet spots and tourist attractions, enabling the calculation of ratings for each spot. Leveraging these ratings, we constructed a walking route recommendation system. Furthermore, we conducted an experiment to compare the routes suggested by using the proposed system, considering nearby spots, with the shortest route.**

***Index Terms*—Walking Assistance, Review Analysis, Route Recommendation, Healthcare**

## I. Introduction

In recent years, due to the health and fitness trend, as well as the need to combat physical inactivity caused by the COVID-19 pandemic[1] [2], there has been a growing awareness of walking as a means of staying healthy. However, many individuals find it challenging to derive enjoyment from walking, making it difficult to sustain their exercise routines [1]. While existing pedestrian navigation systems recommend walking routes, these systems primarily focus on providing the shortest route to a user's specified destination, without a primary goal of making the act of walking an enjoyable experience.

To address this issue, we are dedicated to the development of a walking support system that not only ensures safety but also enhances the pleasure of walking [2]. Our approach involves the utilization of data sources such as user reviews, geotagged tweets on Twitter, traffic information, accident data, and more, to formulate a walking route recommendation method that takes into account both positive and negative user sentiments.

In this paper, we conduct an analysis of user reviews pertaining to gourmet spots and tourist attractions. We propose an algorithm for evaluating these spots, concurrently developing a system that recommends walking routes based on these computed evaluations. Subsequently, we conduct an experiment to compare the routes recommended by our system, which considers spot evaluations, against the shortest routes available.

While we are considering evaluating a diverse range of spots in the future, this paper specifically focuses on user reviews related to gourmet spots and tourist attractions. Leveraging these spot reviews makes it easier to account for user preferences and, more importantly, we believe it can help users find enjoyment in walking, thereby boosting motivation.

In the following sections, we will discuss related research in Section II, the methods used for spot area evaluation and walking route cost calculation (Section III), the construction of our walking route recommendation system (Section IV), an experiment evaluating both the recommended routes and the system's usability (Section V), and finally, we will conclude our findings in Section VI.

[1]https://www.mext.go.jp/sports/
[2]https://www.dlri.co.jp/pdf/ld/2020/wt2005b.pdf

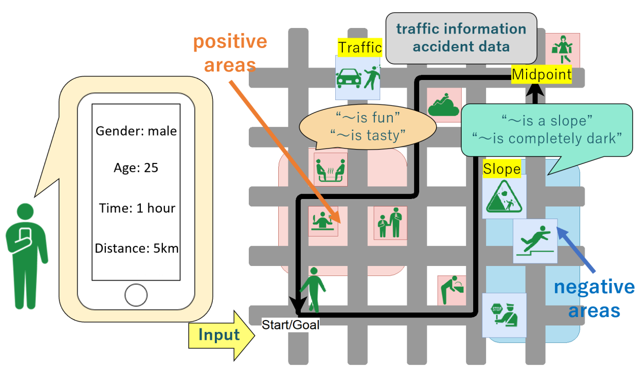


Fig. 1. Overview of the walking route recommendation system.

## II. Related Work

In the context of engaging in walking, the aspect of "motivation" to initiate or sustain this activity holds paramount significance. Walking, being a form of exercise, inherently entails a certain degree of physical exertion. It is a common experience for individuals to associate walking with sensations of hardship or boredom, which can pose challenges in terms of motivation and persistence.

Maeda and colleagues have undertaken research in this domain, proposing a method for recommending walking routes that do not impose excessive physical strain on users [3]. Their approach incorporates gradient data, heart rate information, and geotagged tweets. However, their methodology primarily relies on the quantity of geotagged tweets and does not delve into the content of these tweets. Consequently, this approach runs the risk of including tweets with negative sentiments, such as "dreary" or "dirty," as well as tweets with content that is neither overtly positive nor negative, solely based on the volume of tweets.

Daniele and his team have employed machine learning to determine user preferences based on a pair of photographs, discerning which of the two is more appealing and what type of routes users prefer [4]. This approach goes beyond conventional navigation systems that recommend only the shortest route, instead suggesting routes that are aesthetically pleasing. However, it is worth noting that their methodology does not take into account factors such as traffic information, accident data, or gradient data, which are crucial for ensuring sufficient safety in route recommendations.

Kim and colleagues have proposed a method that avoids areas with extremely negative sentiments inferred from real-time geotagged tweets and finds routes that are slightly longer but safer and more enjoyable than the shortest distance [5]. They also explored route recommendations that circumvent crime-prone areas, as there was a significant correlation between crime rates in the Chicago city portal's crime history data and areas with a high volume of negative tweets. However, their research does not account for traffic information.

Johnson et al. created three types of routes: scenic routes emphasizing beauty, safety routes prioritizing safety, and simple routes emphasizing ease of navigation [6]. They compared these routes with conventional route recommendation methods. However, their study focuses on creating routes emphasizing different aspects and does not recommend routes tailored specifically to individual walking users.

Bhumika and co-authors developed a framework called MARRS, a multi-objective route recommendation system considering safety, and conducted effectiveness verification [7]. Unlike previous methods, they extracted specific crime features from multiple data sources and incorporated them into a learning model for route recommendations. However, they did not conduct evaluation experiments using actual road networks, leaving the effectiveness of their approach uncertain.

## III. Walking Route Recommendation Method

In this section, we discuss the recommendation method for walking routes that users would want to take. Firstly, in Section III-A, we provide an overview of the walking route recommendation. Then, in Section III-B, we delve into the analysis of user reviews of spots and calculate spot ratings based on the results. Finally, in Section III-C, we describe the methodology for creating the route search algorithm.

### A. Overview of the walking route recommendation system

In Figure 1, we present an overview of the walking route recommendation system. Users are initially asked to provide their personal information, as well as preferences for walking distance and duration. Within these specified parameters, the system aims to recommend walking routes that avoid areas with high levels of risk and discomfort, commonly referred to as negative areas. Conversely, the system seeks to guide users through positive areas that they would find enjoyable and aesthetically pleasing. Data sources utilized in this system include spot reviews, geotagged tweet content, traffic information, accident data, and more. In this study, we specifically focus on user reviews related to gourmet spots and tourist attractions, calculate ratings for each spot, and employ this information for route recommendations.

### *B. The method for calculating the overall spot ratings*

In this section, we will explain the method for calculating the overall spot ratings. For this research, we utilized data from the travel review website Jalan[3]. Let $S_i$ represent a spot, and its final rating, denoted as $Score(S_i)$, can be expressed using Equation (1):

$$Score(S_i) = \frac{RAve(S_i) + AScore(S_i)}{2} \tag{1}$$

Here, $Score(S_i)$ represents the final rating of spot $S_i$, which is the average of two values: the average rating of spot $S_i$ by other users, denoted as $RAve(S_i)$, and the average rating of spot $S_i$ based on our review analysis, denoted as $AScore(S_i)$. The calculation for $AScore(S_i)$ is detailed in Equation (2).

$$\begin{aligned} AScore(S_i) = \frac{1}{Rn(S_i)} \sum_{U_j=1}^{Rn(S_i)} (mid + (UScore(U_j) \\ -mid) \times UTrust(U_j)) \end{aligned} \tag{2}$$
$$(1 \leq UScore(U_j) \leq 5, 0 \leq UTrust(U_j) \leq 1)$$

The estimated spot rating $AScore(S_i)$, which can be inferred from all reviews, is an average of the inferred spot ratings $UScore(U_j)$ from any review user $U_j$ who posted a review on the spot's page. However, this calculation takes into account the dependability of the review user $U_j$, denoted as $UTrust(U_j)$. $UTrust(U_j)$ ranges from 0 to 1, with higher values indicating greater dependability. As $UTrust(U_j)$ increases, the value of $UScore(U_j)$ is maintained, whereas lower values of $UTrust(U_j)$ converge $UScore(U_j)$ toward the median of the spot rating range, denoted as $mid$.

In the following Section III-B1, we will describe the methodology for calculating $UScore(U_j)$ inferred from reviews, and in Section III-B2, we will detail the calculation method for the dependability of review users, $UTrust(U_j)$.

*1) The spot rating inferred from the reviews:* The estimated spot rating $UScore(U_j)$ inferred from the reviews posted by review user $U_j$ can be expressed using Equation (3):

$$\begin{aligned} UScore(U_j) = (GScore(U_j) + \\ RAnalysis(U_j))/2 \end{aligned} \tag{3}$$

[3]https://www.jalan.net/

$UScore(U_j)$ is calculated as the average of $GScore(U_j)$, which represents the user's rating of the spot, and $RAnalysis(U_j)$, which is the sentiment analysis value of the review content. $GScore(U_j)$ is primarily the average of the five-point ratings within the review, including the local atmosphere, taste, price, service, and ambiance. However, in some cases, these specific ratings might not be explicitly mentioned in the reviews. In such instances, the overall rating of the spot, which is also a five-point rating, is used instead.

$RAnalysis(U_j)$ is computed using the sentiment analysis tool Microsoft Azure Text Analytics[4]. This value ranges from 0 to 1, where 0 indicates a negative sentiment in the review text, and 1 indicates a positive sentiment. To bring this value into a consistent range with the five-point rating $GScore(U_j)$, it is multiplied by 5.

*2) The dependability of review user:* The dependability of review user $U_j$, denoted as $UTrust(U_j)$, can be expressed using Equation (4):

$$\begin{aligned} UTrust(U_j) = WP \times WPdep(U_j) + \\ C \times CExi(U_j) + T \times TExi(U_j) + \\ N \times NExi(U_j) + F \times FExi(U_j) + \\ L \times LExi(U_j) \end{aligned} \tag{4}$$
$$(WP + C + T + N + F + L = 1)$$

In this equation, $WPdep(U_j)$ represents the time interval between the date when the spots mentioned in the reviews were visited and the date when the reviews were posted. $CExi(U_j)$, $TExi(U_j)$, $NExi(U_j)$, $FExi(U_j)$, and $LExi(U_j)$ indicate the presence or absence of various factors related to the reviews, including congestion, duration of stay, number of visitors, family composition, and the presence of links to the review user's page. These factors are used to measure the dependability of the review user from various perspectives.

The coefficients $WP$, $C$, $T$, $N$, $F$, and $L$ are weights assigned to each of these factors, and they sum up to 1. The closer the value of $UTrust(U_j)$ is to 1, the higher the dependability of the user. $WPdep(U_j)$ decreases by 1 for each year of the time interval.

It is important to note that $UTrust(U_j)$ may become negative based on the values of these factors, in which case it is set to 0 to ensure that it remains within a valid range.

[4]https://azure.microsoft.com/ja-jp/services/cognitive-services/text-analytics/

### C. Walking route cost calculation method

In this section, we will explain how to calculate the walking route cost using the values computed in the previous section. First, we obtained approximately 3500 pedestrian nodes around Kyoto Shijo from OpenStreetMap[5]. These nodes contain latitude and longitude information, as well as IDs for identifying roads and the ability to determine adjacent nodes. We use this data to construct the road network.

Simultaneously, we perform a shortest path search using Dijkstra's algorithm and draw the route obtained using the Google Maps API[6] on Google Maps. Then, based on the algorithm proposed in Section III-A and spot ratings, we update the cost of roads calculated using Dijkstra's algorithm. Specifically, we use Equation (5) to update the road cost.

$$Cost^{eva_i} = Cost^{dis_i} \times NScore \tag{5}$$

The cost of road $i$, denoted as $Cost^{eva_i}$, is calculated by multiplying the actual distance cost of road $i$, $Cost^{dis_i}$, by the spot evaluation in the vicinity of road $i$, $NScore$, as shown in Equation (5).

The distance cost $Cost^{dis_i}$ is determined using the haversine formula based on the latitude and longitude information of the adjacent nodes, providing the actual distance between them.

The spot evaluation in the vicinity, $NScore$, is computed using the spot's final rating values obtained in Section III-B, as described by Equation (6).

$$NScore = \prod_{sp \in SP(i)} \{1 + P(mid - Score(sp))\} \tag{6}$$

In this equation, $NScore$ represents the evaluation of spots around road $i$. It's computed based on the ratings of spots $sp$ belonging to the set of spots around road $i$, denoted as $SP(i)$. $Score(sp)$ represents the rating of a spot $sp$, and $mid$ is the median value of spot ratings. The difference between $Score(sp)$ and $mid$ is computed, then this difference is adjusted using a parameter and 1 is added to it. This adjusted value is then multiplied for each spot $sp$ in $SP(i)$ to compute the final $NScore$.

When $Score(sp)$ is greater than $mid$, $NScore$ becomes less than 0, causing the cost of road $i$, $Cost^{eva_i}$, to be less than the actual distance cost $Cost^{dis_i}$. On the other hand, when $Score(sp)$ is less than $mid$, $NScore$ becomes greater than 0, resulting in the cost of road $i$, $Cost^{eva_i}$, being greater than the actual distance cost $Cost^{dis_i}$. As a consequence, routes with lower costs are more likely to be recommended.

The set of spots around road $i$, $SP(i)$, is defined as spots with a distance of 50 meters or less from road $i$.

[5]https://www.openstreetmap.org/

[6]https://developers.google.com/maps/documentation?hl=ja/

Fig. 2. System in walking mode.

## IV. Implementation

In this section, we will describe the prototype of the walking route recommendation system. This system has been constructed using the Google Maps API. After specifying the starting point and destination for walking, it simultaneously displays Google Street View images and Google Maps. Clicking the "Go" button will update the Google Street View image and place a red marker on the Google Map, indicating users' current location, as shown in Figure 2.

This setup allows users to navigate while also viewing the map, enhancing the walking experience. On the map, users can find information about nearby spots, and on the right side of the screen, users can access details about each spot. This information includes the name of the establishment, its genre, rating, photos, and reviews. By clicking the "Review" button, users can read reviews, as illustrated in Figure 3.

## V. Evaluation

In this section, we will describe the evaluation experiment conducted using the system. Thirteen university students participated as subjects. They were asked to use the system constructed in Section 4 and evaluate the routes generated using the recommendation method from Section 3, as well as the usability of the system.

The routes used in this experiment had two starting points in Kyoto, Japan: Shijo-Ohashi (referred to as

Fig. 3. System in review display mode.

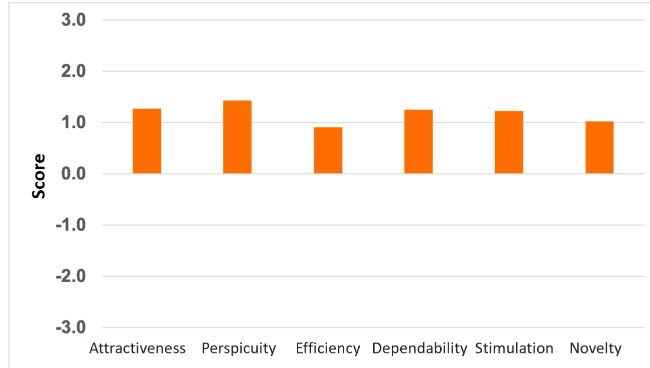


Fig. 4. The results of UEQ.

Departure-Destination 1) and Shijo-Karasuma (referred to as Departure-Destination 2). For each starting point, three types of routes were presented: the shortest route (referred to as Route 1), the route generated using the recommendation method from Section 3 (referred to as Route 2), and the route generated using the recommendation method from Section 3 considering only positive spots and not processing negative spots (referred to as Route 3). In total, six routes were presented to each participant.

Participants were asked to rank these routes based on whether they felt motivated and whether the route would encourage them to continue walking. They were also asked to provide written explanations for their rankings.

Furthermore, the usability of the system was evaluated using two evaluation methods: the User Experience Questionnaire (UEQ) [8] and the System Usability Scale (SUS) [9]. The participants were asked to complete these questionnaires, and they were also interviewed and asked to provide written feedback about the strengths and weaknesses of the system.

UEQ, developed by Laugwitz, is a usability and user experience questionnaire that measures aspects such as efficiency, perspicuity, and dependability, as well as user experience aspects like novelty and stimulation. The scores range from -3.0 to 3.0, with values between -0.8 and 0.8 considered neutral, values higher than this range indicating positive evaluations, and values lower than this range indicating negative evaluations. UEQ is available in over 30 languages, including Japanese.

SUS, developed by John Brooke, is a numerical measure of system usability. It uses a scale with 100 as the reference point, with an average score of 68. A Japanese-translated version of SUS, created specifically for this experiment, was used.

Table I presents the average rankings provided by participants for each route from Departure-Destination 1 and 2. Figure 4 shows the results of the User Experience Questionnaire (UEQ).

TABLE I
AVERAGE RANK RESULTS OF ROUTE EVALUATION.

| | Route1 | Route2 | Route3 |
|---|---|---|---|
| Average Rank for Departure-Destination 1 | 1.8th | 2.6th | 1.6th |
| Average Rank for Departure-Destination 2 | 2.6th | 1.8th | 1.6th |

In Table I, we observed that Route 3 received the highest evaluation, indicating that the route recommended using the proposed method is more suitable for walking than the shortest route. However, when comparing Route 2 and Route 3, comments in the questionnaire, such as "I didn't feel a significant difference between Route 2 and 3" and "I overall feel it's a close call," were noted. Additionally, there were fewer people who ranked Route 2 as the worst (3rd place) compared to Route 3, somewhat aligning with our expectations.

In Figure 4, we obtained positive evaluations in all categories. Furthermore, when comparing the results with the UEQ of the walking route recommendation system proposed by us previously, our system outperformed it in all aspects. The SUS score of 77.5 also exceeded the average score of 68, indicating that the usability of the system was higher than the previously proposed walking route recommendation system.

Regarding the positive aspects of using the system, users appreciated being able to confirm nearby spots while viewing the actual locations on Google Maps, having clear awareness of their current location with simultaneous access to Google Maps and StreetView, quick access to rating and review information for spots of interest, the opportunity for discovering new spots, easier route planning with information about spots before walking, and the simplicity of operation.

However, there were several areas identified for improvement. Many users expressed the need for improvement in the quality of StreetView images. In some locations, the images were facing walls or showing areas that were not part of the road. These images are determined based on the angle at which they should face, considering the coordinates of the current location and the next point. It is suggested that improving image quality could be achieved by refining the points taken along the route.

Additionally, users provided suggestions for enhancing the spot information section. Specific feedback included making spot ratings more visually understandable using star ratings, highlighting newly appeared spots, removing obvious duplicate spots, providing a way to check for the presence of reviews, and adding a review sorting feature. Users also expressed the desire for more information, such as the posting date of reviews and the opening hours and closing days of spots, indicating the need for evaluating the system from a temporal perspective. Other suggestions included the addition of a back button, increasing the size of the frequently used forward button, and improving the system based on this feedback.

## VI. Conclusion

In this paper, we proposed a method for walking route recommendation aimed at encouraging users to engage in regular walking. To realize this system, we conducted evaluations of gourmet and tourist spots based on user reviews. Using this evaluation, we calculated the walking route costs. We also built a prototype of a route recommendation system designed to support walking activities. Furthermore, we conducted user experiments using this system, gathering feedback on the routes and assessing the system's usability.

In the future, we plan to make several improvements and extensions based on the results of these experiments. This includes reconstructing the road network, considering various departure and destination patterns for route comparisons, expanding the scope of road data collection, enhancing spot evaluation methods by applying them to other data sources like geotagged tweets, assessing the degree of spot evaluation integration into the system, conducting further evaluation experiments considering walking route recommendations, extracting user characteristics while preserving personal privacy, setting walking time preferences, and developing a route recommendation algorithm that takes safety aspects into account by incorporating traffic and accident data. Ultimately, our goal is to create a practical and effective route recommendation system for walking enthusiasts.

## Acknowledgment

The work carried out in this paper is supported by the JSPS KAKENHI research grant (20H04293, 22H03700, 22K19837). And this is also a product of research activity of Institute of Advanced Technology, Center for Sciences towards Symbiosis among Human, Machine and Data which was financially supported by the Kyoto Sangyo University Research Grants, (M2301).

## References

[1] Ekkekakis, P., Parfitt, G., & Petruzzello, S. J. (2011). The pleasure and displeasure people feel when they exercise at different intensities: decennial update and progress towards a tripartite rationale for exercise intensity prescription. Sports medicine, 41, 641-671.

[2] Yamauchi, K., Siriaraya, P., Li D., Kawai, Y., & Nakajima, S. (2022). Validation of a Nearby Spot Evaluation Method for Walking Route Recommendation (in Japanese). DEIM Forum 2022, A31-2.

[3] Maeda, Y., Kiriu, T., Siriaraya, P., Kawai, Y., & Nakajima, S. (2018). Smart Walking Navigation System Considering Physical and Psychological Load (in Japanese). DEIM Forum 2018, H3-5.

[4] Quercia, D., Schifanella, R., & Aiello, L. M. (2014, September). The shortest path to happiness: Recommending beautiful, quiet, and happy routes in the city. In Proceedings of the 25th ACM conference on Hypertext and social media (pp. 116-125).

[5] Kim, J., Cha, M., & Sandholm, T. (2014, April). Socroutes: safe routes based on tweet sentiments. In Proceedings of the 23rd International Conference on World Wide Web (pp. 179-182).

[6] Johnson, I., Henderson, J., Perry, C., Schöning, J., & Hecht, B. (2017). Beautiful… but at what cost? An examination of externalities in geographic vehicle routing. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(2), 1-21.

[7] Bhumika, & Das, D. (2022, September). MARRS: A Framework for multi-objective risk-aware route recommendation using Multitask-Transformer. In Proceedings of the 16th ACM Conference on Recommender Systems (pp. 360-368).

[8] Laugwitz, B., Held, T., & Schrepp, M. (2008). Construction and evaluation of a user experience questionnaire. In HCI and Usability for Education and Work: 4th Symposium of the Workgroup Human-Computer Interaction and Usability Engineering of the Austrian Computer Society, USAB 2008, Graz, Austria, November 20-21, 2008. Proceedings 4 (pp. 63-76). Springer Berlin Heidelberg.

[9] Brooke, J. (1996). SUS: a "quick and dirty" usability. Usability evaluation in industry, 189(3), 189-194. London: Taylor & Francis.